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FSE-RBFNNs-Based Adaptive Tracking Control of Hypersonic Flight Vehicles with Uncertain Periodic Time-Varying Disturbances

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Abstract: This work for the first time develops a neuro-adaptive control strategy for an extended class of longitudinal dynamics of hypersonic flight vehicles (HFVs). To handle with the design difficulty that the uncertain time-varying disturbances appear implicitly in HFVs dynamics, a new function approximator is designed by incorporating the fourier series expansion (FSE) into the radial basis function neural networks (RBFNNs). An integral term and a linear term are, respectively, constructed to speed up the convergence rate and compensate for the negative effects caused by approximation errors. It is rigorously proved that all closed-loop signals are semi-globally uniformly ultimately bounded (SGUUB). Simulation results verify the effectiveness of the proposed control methodology.

Key Words: Hypersonic Flight Vehicles, FSE-RBFNNs-Based Approximator, Uncertain Periodic Disturbances

1 Introduction

Several research on HFVs have been carried out by worldwide institutes due to its advantages of high-speed and low cost especially in the near-space transportation [1]. For example, a feedback linearization method is employed for steering the velocity and altitude to the reference trajectories in [2], overcoming the design difficulty arising from the couplings between the engine and the flight dynamics of longitudinal system. By introducing an auxiliary system, a robust adaptive dynamic surface control method is proposed to deal with the actuator saturation problem in [3]. In [4], a command filtered back-stepping control technique is presented for the longitudinal dynamics to filter the virtual control law, which alleviates the computation burden in the sense that no calculation of the derivative of virtual control law is required. Besides, in order to deal with small angle values encountered in engineering practice, the reconstruction strategies of flight track angle and angle of attack are provided in [5]. However, above mentioned results are merely based on the ideal HFVs dynamics in which disturbance terms were not taken into account.

It is well-recognized that perturbations inevitably occur in HFVs dynamics due to the presence of uncertain aerodynamic parameters and unknown time-varying aerodynamics. The main obstacle in dealing with such perturbations lies in the fact that they influence the system in a nonlinear and unknown manner [6]. To counteract this barrier, fuzzy adaptive control [7]-[10], multilayer nerual networks (MNNs) [11] and RBFNNs [12]-[14] have been exploited for estimating those system nonlinearities. More specifically, in [10], a fuzzy-approximation-based adaptive control method is proposed to solve the non-smooth issue while designing disturbance observer. The MNNs and the backstepping technology are combined in [11] to achieve closed-loop stability for strict-feedback nonlinear systems. In [13], a RBFNNs-based adaptive control strategy is developed to stabilize a class of nonlinear high-order dynamics. Nevertheless, as far as we know, owing to the design difficulty, no control approach known has been proposed for the dynamics of HFVs with time-varying periodic disturbances, which impact the flight quality seriously and cannot be well handled using conventional control scheme. These reasons motivate us to explore new design going beyond the existing methods. The main contributions of this study are given in the following three-folds:

1) To our best knowledge, this should be the first work addressing tracking control problem for HFVs subject to unknown periodically time-varying disturbances.
2) Compared to the standard designs in [15]-[17], an integral term is devised to enhance the convergence rate of tracking errors, and a linear term is constructed to compensate for approximation errors.
3) A new approximator consisting of FSE and RBFNNs is introduced to model each suitable uncertain disturbance, where FSE is utilized to estimate the periodic perturbance. Then the estimated values can be regarded as inputs of RBFNNs to approximate the uncertain dynamics of HFVs.

The rest of this paper is organized as: the longitudinal dynamics of HFVs, the FSE-RBFNNs-based approximator as well as preliminaries are provided in section 2. Section 3 presents the neuro-adaptive control design. Stability analysis is given in section 4 and section 5 provides the simulation results, followed by the conclusion in section 6.

2 Problem Formulation and Preliminaries

2.1 Hypersonic Flight Vehicle Dynamics

The longitudinal dynamic model of HFVs under study is given as [18]-[19]

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$$\dot{V} = \frac{T\cos(\theta-\gamma) - D}{m} - g\sin\gamma, \tag{1}$$

$$\dot{h} = V\sin\gamma, \tag{2}$$

$$\dot{\gamma} = \frac{T\sin(\theta-\gamma) + L}{mV} - \frac{g\cos\gamma}{V}, \tag{3}$$

$$\dot{\theta} = Q, \tag{4}$$

$$\dot{Q} = \frac{M + \tilde{\psi}_1\ddot{\eta}_1 + \tilde{\psi}_2\ddot{\eta}_2}{I_{yy}}, \tag{5}$$

$$\ddot{\eta}_1 = -2\zeta_1\omega_1\dot{\eta}_1 - \omega_1^2\eta_1 + N_1 - \frac{\tilde{\psi}_1 M}{I_{yy}} - \frac{\tilde{\psi}_1\tilde{\psi}_2\ddot{\eta}_2}{I_{yy}}, \tag{6}$$

$$\ddot{\eta}_2 = -2\zeta_2\omega_2\dot{\eta}_2 - \omega_2^2\eta_2 + N_2 - \frac{\tilde{\psi}_2 M}{I_{yy}} - \frac{\tilde{\psi}_2\tilde{\psi}_1\ddot{\eta}_1}{I_{yy}}, \tag{7}$$

where V, h, γ, θ and Q represent the velocity, altitude, flight path angle, pitch angle and pitch rate, respectively; I_{yy} is the moment of inertia; η_i denotes the ith elastic mode; ζ_i, ω_i and ψ_i are the damping ratio, the natural frequency and the constrained beam coupling constant for η_i; the thrust force T, the drag force D, the lift force L, the pitching moment M, the first generalized force N_1 and the second generalized force N_2 are defined as

$$\begin{aligned}
T =&\beta_1(h,\bar{q})\delta_\Phi\alpha^3 + \beta_2(h,\bar{q})\alpha^3 + \beta_3(h,\bar{q})\delta_\Phi\alpha^2 \\
&+ \beta_4(h,\bar{q})\alpha^2 + \beta_5(h,\bar{q})\delta_\Phi\alpha + \beta_6(h,\bar{q})\alpha \\
&+ \beta_7(h,\bar{q})\delta_\Phi + \beta_8(h,\bar{q}), \\
D =&\bar{q}SC_D^{\alpha^2}\alpha^2 + \bar{q}SC_D^{\alpha}\alpha + \bar{q}SC_D^{\delta_e^2}\delta_e^2 + \bar{q}SC_D^{\delta_e}\delta_e + \bar{q}SC_D^0, \\
M =&z_T T + \bar{q}S\bar{c}C_{M,\alpha}^{\alpha^2}\alpha^2 + \bar{q}S\bar{c}C_{M,\alpha}^{\alpha}\alpha + \bar{q}S\bar{c}C_{M,\alpha}^0 + \bar{q}S\bar{c}c_e\delta_e, \\
L =&\bar{q}SC_L^\alpha\alpha + \bar{q}SC_L^{\delta_e}\delta_e + \bar{q}SC_L^0, \\
N_1 =&N_1^{\alpha^2}\alpha^2 + N_1^\alpha\alpha + N_1^0, \\
N_2 =&N_2^{\alpha^2}\alpha^2 + N_2^\alpha\alpha + N_2^{\delta_e}\delta_e + N_2^0, \\
\bar{q} =&\frac{\bar{\rho}V^2}{2}, \quad \bar{\rho} = \bar{\rho}_0\exp\left(\frac{h_0 - h}{h_s}\right),
\end{aligned}$$

where Φ is the fuel equivalence ratio, δ_e is the elevator angular deflection, and readers can consult [18] for more information about other system parameters.

Remark 1: Model (1) has been widely used in [1]-[5]: it consists of five rigid body states, two flexible states, and two control inputs. It is worth mentioning that δ_e is mainly affected by the angle of attack α, whereas Φ is primarily affected by the thrust T, which is consistent with the model decomposition shown here and afterward.

The conventional velocity subsystem of HFVs is [5]

$$\dot{V} = f_V + g_V\Phi, \tag{8}$$

where $f_V = \frac{\bar{q}SC_D^{\alpha^2}\alpha^2 + \bar{q}SC_D^0}{m} - g\sin\gamma + \frac{\cos\alpha}{m}\left[\beta_2(h,\bar{q})\alpha^3 + \beta_4(h,\bar{q})\alpha^2 + \beta_6(h,\bar{q})\alpha + \beta_8(h,\bar{q})\right]$, $g_V = \frac{\cos\alpha}{m}\left[\beta_7(h,\bar{q}) + \beta_3(h,\bar{q})\alpha^2 + \beta_1(h,\bar{q})\alpha^3\right]$.

The velocity subsystem considered in our paper (embedding unknown time-varying disturbances d_V) is given by

$$\dot{V} = f_V(\gamma,\theta,d_V) + g_V(\gamma,\theta,d_V)\Phi. \tag{9}$$

The system nonlinearities $f_V(\gamma,\theta,d_V)$ and $g_V(\gamma,\theta,d_V)$ are unknown due to the existence of unknown aerodynamic parameters and unknown external disturbance.

Define the altitude error $e_h = h - h_{ref}$, and the flight path angle command is devised as

$$\gamma_{ref} = \arcsin\left[\frac{1}{V}\left(-k_h e_h - k_i\int e_h dt + \dot{h}_{ref}\right)\right], \tag{10}$$

where h_{ref} is the reference altitude command, k_h and k_i are positive design parameters. Note the fact that e_h will converge to zero exponentially as $\gamma \to \gamma_{ref}$ according to [20].

The conventional altitude subsystem of HFVs is [5]

$$\begin{cases} \dot{\gamma} = f_\gamma + g_\gamma\theta, \\ \dot{\theta} = Q, \\ \dot{Q} = f_Q + g_Q\delta_e, \end{cases} \tag{11}$$

where $f_\gamma = \frac{\bar{q}S\left(C_L^0 - C_L^\alpha\gamma\right) + T\sin\alpha}{mV} - \frac{g\cos\gamma}{V}$, $g_\gamma = \frac{\bar{q}SC_L^\alpha}{mV}$, $f_Q = z_T T + \frac{\bar{q}S\bar{c}C_{M,\alpha}(\alpha)}{I_{yy}}$ and $g_Q = \frac{\bar{q}S\bar{c}c_e}{I_{yy}}$.

We consider unknown periodic disturbances $d_\gamma(t)$ and $d_Q(t)$ with $d_\gamma(t+T_\gamma) = d_\gamma(t)$ and $d_Q(t+T_Q) = d_Q(t)$ in the altitude subsystem. Then, the altitude subsystem can be expressed by

$$\begin{cases} \dot{\gamma} = f_\gamma(\gamma,d_\gamma) + g_\gamma(\gamma,d_\gamma)\theta, \\ \dot{\theta} = Q, \\ \dot{Q} = f_Q(\gamma,\theta,Q,d_Q) + g_Q(\gamma,\theta,Q,d_Q)\delta_e. \end{cases} \tag{12}$$

Following similar analysis to velocity subsystem, system nonlinearities $f_\gamma(\gamma,d_\gamma)$, $g_\gamma(\gamma,d_\gamma)$, $f_Q(\gamma,\theta,Q,d_Q)$ and $g_Q(\gamma,\theta,Q,d_Q)$ are unknown continuous functions.

Remark 2: In contrast with the state-of-the-art [1]-[5],[23] and [24], the most advanced peculiarity of this work lies in taking unknown periodic disturbances into account in velocity (9) and altitude (12) subsystems. To tackle this issue, a new approximator composed by FSE and RBFNNs is employed to estimate unknown system nonlinearities $f_\gamma(\gamma,d_\gamma)$, $g_\gamma(\gamma,d_\gamma)$, $f_Q(\gamma,\theta,Q,d_Q)$ and $g_Q(\gamma,\theta,Q,d_Q)$.

Assumption 1 [1]: The reference trajectory γ_{ref} is a sufficiently smooth function with respect to t, and there exists a positive constant B_0 such that $\prod_0 := \left\{(\gamma_{ref},\dot{\gamma}_{ref}) | \gamma_{ref}^2 + \dot{\gamma}_{ref}^2 \le B_0^2\right\}$.

Assumption 2 [5]: The signs of g_γ and g_Q are assumed known a priori. Without loss of generality, we assume there exsit positive constants $g_{\gamma m}$, $g_{\gamma M}$, g_{Qm} and g_{QM} such that $g_{\gamma m} \le |g_\gamma| \le g_{\gamma M}$ and $g_{Qm} \le |g_Q| \le g_{QM}$.

Remark 3: In altitude subsystem (12), the control gain function $g_\gamma = \frac{\bar{q}SC_L^\alpha}{mV}$ is changing continuously with respect to $V \in \Omega_V$ and d_γ, where Ω_V is a compact set and d_γ is a bounded disturbance, thus continuous function $g_\gamma(\gamma,d_\gamma)$ is also bounded according to extreme value theorem [16]. Similar reasoning results in the boundedness of $g_Q(\gamma,\theta,Q,d_Q)$.

Notation: Throughout this paper, $||\cdot||$ represents the Euclidean norm of a vector, $||\cdot||_F$ denotes the Frobenius norm of a matrix, $|\cdot|_1$ denotes the 1-norm of a vector, $\lambda_{max}(A)$ and $\lambda_{min}(A)$ are the largest and smallest eigenvalues of a square matrix A, respectively.

2.2 FSE-RBFNNs-Based Approximator

We employ the RBFNNs and FSE to construct the composite approximator, $d(t) = [d_1, \ldots, d_m]^T \in \Omega_m \subset R^m$ is an unknown disturbance vector of known period T in compact set Ω_m. The unknown time-varying periodic disturbances can be estimated by FSE in the form of [21]

$$d(t) = S^T \phi(t) + \delta_d(t), \quad ||\delta_d|| \leq \bar{\delta}_d \tag{13}$$

where $S = [s_1, \ldots, s_m] \in R^{q\times m}$ is a constant matrix with $s_i \in R^q$ being a vector consisting of the first q coefficients of the FSE of d_i (q is an odd integer), δ_d is the truncation error with upper bound $\bar{\delta}_d$, $\phi(t) = [\phi_1(t), \cdots, \phi_q(t)]^T$ with $\phi_1(t) = 1$, $\phi_{2j}(t) = \sqrt{2}\sin(2\pi jt/T)$, $\phi_{2j+1}(t) = \sqrt{2}\cos(2\pi jt/T)$, $j = 1, \ldots, (q-1)/2$.

The RBFNNs are used to approximate the unknown continuous function [22] as

$$h(u) = W^{*T}\psi(u) + \mu, \tag{14}$$

where $u \in \Omega_u \subset R^n$ is the input vector, n is input dimension of neural network; $\psi(u) \in R^l$ is the basis function vector, $l > 1$ is the node number of neural network; μ is approximation error satisfying $0 < |\mu| < \mu^*$; $W^* \in R^l$ is the optimal weight vector.

The unknown time-varying periodic disturbances and the measured states χ_i of HFVs dynamics are taken as inputs, in that we assume V, h, γ, θ and Q are measurable and take periodic disturbances in the form of (13), thus, the unknown function can be expressed as

$$h_i(\chi_i, d_i) = W_i^{*T}\psi\left(\chi_i, S_i^T\phi + \delta_{di}\right) + \mu_i. \tag{15}$$

According to (15), we construct a FSE-RBFNNs approximator as

$$G_i(\chi_i, t) = W_i^T\psi\left(\chi_i, S_i^T\phi\right). \tag{16}$$

Then we can obtain

$$\begin{aligned} h_i(\chi_i, d_i) =& W_i^T\psi\left(\chi_i, S_i^T\phi\right) + \delta_i(\chi_i, t) \\ =& G_i(\chi_i, t) + \delta_i(\chi_i, t), \end{aligned} \tag{17}$$

where $\delta_i(\chi_i, t)$ is the approximate error satisfying $0 < |\delta_i(\chi_i, t)| < \bar{\delta}$ [15].

Lemma 1 [15]: Note that, in approximator (16), W_i and ψ_i are unknown and need to be estimated, the estimation errors of (16) can be expressed as:

$$\begin{aligned} & W_i^T\psi\big(\chi_i, S_i^T\phi\big) - \hat{W}_i^T\psi\big(\chi_i, \hat{S}_i^T\phi\big) \\ &= \tilde{W}_i^T\big(\psi_i\big(\chi_i, \hat{S}_i^T\phi\big) - \psi'\big(\chi_i, \hat{S}_i^T\phi\big)\hat{S}_i^T\phi\big) \\ &\quad + \hat{W}_i^T\psi'\big(\chi_i, \hat{S}_i^T\phi\big)\tilde{S}_i^T\phi + \kappa_i. \end{aligned} \tag{18}$$

where $\hat{W}_i$ and $\hat{S}_i$ are estimates of W_i and S_i. Further, define the weight estimate errors $\tilde{W}_i = W_i - \hat{W}_i$, $\tilde{S}_i = S_i - \hat{S}_i$ and denote $\hat{\psi} = \psi\big(\chi, \hat{S}^T\phi\big)$ and $\hat{\psi}' = \psi'(\chi, \hat{S}^T\phi)$ for brevity.

The residual term κ_i is bounded by

$$\begin{aligned} |\kappa_i| \leq \bar{\kappa}_i =& ||S_i||_F||\phi\hat{W}_i^T\psi'(\chi_i, \hat{S}_i^T\phi)||_F \\ & + ||W_i||\,||\psi'(\chi_i, \hat{S}_i^T\phi)\hat{S}_i^T\phi|| + |W_i|_1, \end{aligned} \tag{19}$$

where $\bar{\kappa}_i$ is a positive constant.

The longitudinal motion is decomposed into altitude subsystem and velocity subsystem in this paper. In the altitude subsystem, an adaptive controller based on FSE-RBFNNs approximator is proposed to achieve the altitude tracking. Moreover, we simply use proportion-integration-differention (PID) control, displayed in simulations, to ensure the velocity tracking in the velocity subsystem.

3 Neuro-Adaptive Control Design

Step 1: Define the tracking error as $e_\gamma = \gamma - \gamma_{ref}$, the derivative of e_γ is

$$\dot{e}_\gamma = \dot{\gamma} - \dot{\gamma}_{ref} = g_\gamma(\gamma, d_\gamma)\theta + f_\gamma(\gamma, d_\gamma) - \dot{\gamma}_{ref}. \tag{20}$$

The form of estimate function is

$$h_\gamma(\chi_\gamma, d_\gamma) = g_\gamma(\gamma, d_\gamma)^{-1}\Big[f_\gamma(\gamma, d_\gamma) - \dot{\gamma}_{ref}\Big]. \tag{21}$$

Substituting (21) into (20) yields

$$\dot{e}_\gamma = g_\gamma(\gamma, d_\gamma)\Big[\theta + h_\gamma(\chi_\gamma, d_\gamma)\Big], \tag{22}$$

where $\chi_\gamma = [\gamma, \dot{\gamma}_{ref}]^T$.

Construct the virtual control law α_γ and adaptive law as

$$\alpha_\gamma = -n_\gamma\Big(\frac{\mu_\gamma}{2} + k_\gamma\Big)e_\gamma - n_\gamma c_\gamma\int_0^t e_\gamma d\tau - \hat{W}_\gamma^T\hat{\psi}_\gamma, \tag{23}$$

$$\begin{cases} \dot{\hat{S}}_\gamma = \Gamma_{S_\gamma}\left[e_\gamma\phi\hat{W}_\gamma^T\hat{\psi}_\gamma' - \sigma_\gamma\hat{S}_\gamma\right], \\ \dot{\hat{W}}_\gamma = \Gamma_{W_\gamma}\left[e_\gamma\big(\hat{\psi}_\gamma - \hat{\psi}_\gamma'\hat{S}_\gamma^T\phi\big) - \sigma_\gamma\hat{W}_\gamma\right], \end{cases} \tag{24}$$

where $\Gamma_{S_\gamma} > 0$ and $\Gamma_{W_\gamma} > 0$ are adaptive gains, $k_\gamma > 0$, $\sigma_\gamma > 0$, $c_\gamma > 0$ and $\mu_\gamma > 0$ are design parameters, and $n_\gamma = \text{sign}(g_\gamma(\gamma, d_\gamma))$.

Substituting (23) into (22) gives

$$\begin{aligned} \dot{e}_\gamma =& g_\gamma(\gamma, d_\gamma)\bigg[-n_\gamma\left(\frac{\mu_\gamma}{2} + k_\gamma\right)e_\gamma + \Xi_\gamma \\ & -n_\gamma c_\gamma\int_0^t e_\gamma d\tau + (\theta - \alpha_\gamma)\bigg], \end{aligned} \tag{25}$$

where $\Xi_\gamma = h_\gamma(\chi_\gamma, d_\gamma) - \hat{W}_\gamma^T\hat{\psi}_\gamma$. According to *Lemma 1*, it holds that

$$\Xi_\gamma = \tilde{W}_\gamma^T\left(\hat{\psi}_\gamma - \hat{\psi}_\gamma'\hat{S}_\gamma^T\phi_\gamma\right) + \hat{W}_\gamma^T\hat{\psi}_\gamma'\tilde{S}_\gamma^T\phi_\gamma + \kappa_\gamma + \delta_\gamma, \tag{26}$$

$$\begin{aligned} |\kappa_\gamma| \leq \bar{\kappa}_\gamma =& ||S_\gamma||_F||\phi\hat{W}_\gamma^T\hat{\psi}_\gamma'||_F \\ & + ||W_\gamma||\,||\hat{\psi}_\gamma'\hat{S}_\gamma^T\phi|| + |W_\gamma|_1. \end{aligned} \tag{27}$$

Step 2: Define tracking error $e_\theta = \theta - \alpha_\gamma$. We have the derivative of e_θ as

$$\dot{e}_\theta = Q - \dot{\alpha}_\gamma. \tag{28}$$

Construct the virtual control law α_θ as

$$\alpha_\theta = -k_\theta e_\theta - c_\theta\int_0^t e_\theta d\tau, \tag{29}$$

where $k_\theta > 0$ and $c_\theta > 0$ are design parameters.

Substituting (29) into (28) gives rise to

$$\dot{e}_\theta = -k_\theta e_\theta - c_\theta\int_0^t e_\theta d\tau - \dot{\alpha}_\gamma + (Q - \alpha_\theta). \tag{30}$$

Step 3: Define tracking error $e_Q = Q - \alpha_\theta$, the derivative of e_Q is

$$\dot{e}_Q = g_Q\left(\gamma, \theta, Q, d_Q\right)\delta_e + f_Q\left(\gamma, \theta, Q, d_Q\right) - \dot{\alpha}_\theta. \tag{31}$$

The form of estimate function is

$$h_Q(\chi_Q, d_Q) = g_Q^{-1}(\gamma, \theta, Q, d_Q)\Big[f_Q(\gamma, \theta, Q, d_Q) - \dot{\alpha}_\theta\Big]. \tag{32}$$

Substituting (32) into (31) results in

$$\dot{e}_Q = g_Q\left(\gamma, \theta, Q, d_Q\right)\Big[\delta_e + h_Q\left(\chi_Q, d_Q\right)\Big], \tag{33}$$

where $\chi_Q = [\gamma, \theta, Q, \dot{\alpha}_\theta]^T$.

Construct the actual control law δ_e and adaptive law as

$$\delta_e = -n_Q\left(\frac{\mu_Q}{2} + k_Q\right)e_Q - n_Q c_Q \int_0^t e_Q d\tau - \hat{W}_Q^T\hat{\psi}_Q, \tag{34}$$

$$\begin{cases} \dot{\hat{S}}_Q = \Gamma_{S_Q}\left[e_Q\phi\hat{W}_Q^T\hat{\psi}'_Q - \sigma_Q\hat{S}_Q\right], \\ \dot{\hat{W}}_Q = \Gamma_{W_Q}\left[e_Q\left(\hat{\psi}_Q - \hat{\psi}'_Q\hat{S}_Q^T\phi\right) - \sigma_Q\hat{W}_Q\right], \end{cases} \tag{35}$$

where $\Gamma_{S_Q} > 0$ and $\Gamma_{W_Q} > 0$ are adaptive gains, $k_Q > 0$, $\sigma_Q > 0$, $c_Q > 0$ and $\mu_Q > 0$ are design parameters, and n_Q =sign$(g_Q(\gamma, \theta, Q, d_Q))$.

Substituting (34) into (33) leads to

$$\begin{aligned} \dot{e}_Q = & g_Q\left(\gamma, \theta, Q, d_Q\right)\Bigg[-n_Q\left(\frac{\mu_Q}{2} + k_Q\right)e_Q + \Xi_Q \\ & -n_Q c_Q \int_0^t e_Q d\tau\Bigg], \end{aligned} \tag{36}$$

where $\Xi_Q = h_Q(\chi_Q, d_Q) - \hat{W}_Q^T\hat{\psi}_Q$. In view of *Lemma 1*, one has

$$\Xi_Q = \tilde{W}_Q^T\left(\hat{\psi}_Q - \hat{\psi}'_Q\hat{S}_Q^T\phi\right) + \hat{W}_Q^T\hat{\psi}'_Q\tilde{S}_Q^T\phi + \kappa_Q + \delta_Q, \tag{37}$$

$$\begin{aligned} |\kappa_Q| \le \bar{\kappa}_Q = & ||S_Q||_F||\phi\hat{W}_Q^T\hat{\psi}'_Q||_F \\ & + ||W_Q||\,||\hat{\psi}'_Q\hat{S}_Q^T\phi|| + |W_Q|_1. \end{aligned} \tag{38}$$

4 Closed-loop Stability Analysis

Theorem 1: Consider the closed-loop system consisting of (12), the virtual control laws (23) and (29), the actual control laws (34), and the adaptive laws (24) and (35). Let Assumptions 1 and 2 hold, then, there exist design parameters $\Gamma_{W_\gamma}, \Gamma_{S_\gamma}, \Gamma_{W_Q}, \Gamma_{S_Q}, k_\gamma, k_\theta, k_Q$ and c_γ, c_θ, c_Q such that: all closed-loop signals are SGUUB and the tracking errors e_* will converge to the following set

$$\Omega_c = \left\{e_* \,||e_*| < C_*\right\}.$$

where $*$ represents γ, θ and Q. C_* is a positive constant that depends on design parameters and adaptive gains.

Proof: Let us take the entire Lyapunov function as

$$\begin{aligned} V = & \frac{e_\gamma^2}{2} + \frac{1}{2}\left(\int_0^t e_\gamma d\tau\right)^2 + \text{tr}\left\{\frac{\tilde{S}_\gamma^T\tilde{S}_\gamma}{2\Gamma_{S_\gamma}}\right\} + \frac{\tilde{W}_\gamma^T\tilde{W}_\gamma}{2\Gamma_{W_\gamma}} \\ & + \frac{e_\theta^2}{2} + \frac{1}{2}\left(\int_0^t e_\theta d\tau\right)^2 + \frac{e_Q^2}{2} + \frac{1}{2}\left(\int_0^t e_Q d\tau\right)^2 \\ & + \text{tr}\left\{\frac{\tilde{S}_Q^T\tilde{S}_Q}{2\Gamma_{S_Q}}\right\} + \frac{\tilde{W}_Q^T\tilde{W}_Q}{2\Gamma_{W_Q}}. \end{aligned} \tag{39}$$

The derivative of V is

$$\begin{aligned} \dot{V} = & e_\gamma\dot{e}_\gamma + e_\gamma\int_0^t e_\gamma d\tau + \text{tr}\left\{\frac{\tilde{S}_\gamma^T\dot{\hat{S}}_\gamma}{\Gamma_{S_\gamma}}\right\} + \frac{\tilde{W}_\gamma^T\dot{\hat{W}}_\gamma}{\Gamma_{W_\gamma}} \\ & + e_\theta\dot{e}_\theta + e_\theta\int_0^t e_\theta d\tau + e_Q\dot{e}_Q + e_Q\int_0^t e_Q d\tau \\ & + \text{tr}\left\{\frac{\tilde{S}_Q^T\dot{\hat{S}}_Q}{\Gamma_{S_Q}}\right\} + \frac{\tilde{W}_Q^T\dot{\hat{W}}_Q}{\Gamma_{W_Q}}. \end{aligned} \tag{40}$$

Substituting (25), (30) and (36) into (40) reaches

$$\begin{aligned} \dot{V} = & g_\gamma\left(\gamma, d_\gamma\right)\Big[-n_\gamma\, k_\gamma\, e_\gamma^2 - n_\gamma c_\gamma e_\gamma\int_0^t e_\gamma d\tau + e_\gamma\,\Xi_\gamma \\ & + \text{tr}\left\{\frac{\tilde{S}_\gamma^T\dot{\hat{S}}_\gamma}{\Gamma_{S_\gamma}}\right\} + \frac{\tilde{W}_\gamma^T\dot{\hat{W}}_\gamma}{\Gamma_{W_\gamma}} - k_\theta e_\theta^2 - c_\theta e_\theta\int_0^t e_\theta d\tau \\ & - \frac{n_\gamma\mu_\gamma e_\gamma^2}{2} + (\theta - \alpha_\gamma)e_\gamma\Big] + e_\gamma\int_0^t e_\gamma d\tau - e_\theta\dot{\alpha}_\gamma \\ & + (Q - \alpha_\theta)\,e_\theta + e_\theta\int_0^t e_\theta d\tau + e_Q\int_0^t e_Q\, d\tau + \frac{\tilde{W}_Q^T\dot{\hat{W}}_Q}{\Gamma_{W_Q}} \\ & + g_Q\left(\gamma, \theta, Q, d_Q\right)\Big[-n_Q k_Q e_Q^2 - n_Q c_Q e_Q\int_0^t e_Q d\tau \\ & + e_Q\Xi_Q\Big] - \frac{n_Q\mu_Q e_Q^2}{2} + \text{tr}\left\{\frac{\tilde{S}_Q^T\dot{\hat{S}}_Q}{\Gamma_{S_Q}}\right\}, \end{aligned} \tag{41}$$

where

$$\begin{aligned} e_\gamma\Xi_\gamma = & \tilde{W}_\gamma^T\big(\psi_\gamma\big(\chi_\gamma, \hat{S}_\gamma^T\phi\big) - \psi'_\gamma\big(\chi_\gamma, \hat{S}_\gamma^T\phi\big)\hat{S}_\gamma^T\phi_\gamma\big)e_\gamma \\ & + \hat{W}_\gamma^T\psi'_\gamma\big(\chi_\gamma, \hat{S}_\gamma^T\phi\big)\tilde{S}_\gamma^T\phi_\gamma e_\gamma + \big(\kappa_\gamma + \delta_\gamma\big)e_\gamma, \end{aligned} \tag{42}$$

$$\begin{aligned} e_Q\Xi_Q = & \tilde{W}_Q^T\big(\psi_Q\big(\chi_Q, \hat{S}_Q^T\phi\big) - \psi'_Q\big(\chi_Q, \hat{S}_Q^T\phi\big)\hat{S}_Q^T\phi\big)e_Q \\ & + \hat{W}_Q^T\psi'_Q\big(\chi_Q, \hat{S}_Q^T\phi\big)\tilde{S}_Q^T\phi e_Q + \big(\kappa_Q + \delta_Q\big)e_Q. \end{aligned} \tag{43}$$

where $e_\theta = \theta - \alpha_\gamma$ and $e_Q = Q - \alpha_\theta$.

Substituting (24), (35), (42) and (43) into (41), we have

$$\begin{aligned} \dot{V} = & g_\gamma(\gamma, d_\gamma)\Big[-n_\gamma k_\gamma e_\gamma^2 - n_\gamma c_\gamma e_\gamma\int_0^t e_\gamma d\tau - \frac{n_\gamma\mu_\gamma e_\gamma^2}{2} \\ & + e_\theta e_\gamma + \left(\kappa_\gamma + \delta_\gamma\right)e_\gamma\Big] + e_\gamma\int_0^t e_\gamma d\tau + \sigma_\gamma\Big(\text{tr}\left\{\tilde{S}_\gamma^T\hat{S}_\gamma\right\} \\ & + \tilde{W}_\gamma^T\hat{W}_\gamma\Big) - k_\theta e_\theta^2 - c_\theta e_\theta\int_0^t e_\theta d\tau - e_\theta\dot{\alpha}_\gamma + e_Q e_\theta \\ & + e_\theta\int_0^t e_\theta d\tau + \sigma_Q\left(\text{tr}\left\{\tilde{S}_Q^T\hat{S}_Q\right\} + \tilde{W}_Q^T\hat{W}_Q\right) + e_Q\int_0^t e_Q d\tau \\ & + g_Q\left(\gamma, \theta, Q, d_Q\right)\Big[-n_Q k_Q e_Q^2 - n_Q c_Q e_Q\int_0^t e_Q d\tau \\ & - \frac{n_Q\mu_Q e_Q^2}{2} + \left(\kappa_Q + \delta_Q\right)e_Q\Big]. \end{aligned} \tag{44}$$

Using Young's inequality leads to

$$\kappa_* e_* - \frac{\mu_* e_*^2}{4} \leq \frac{\kappa_*^2}{\mu_*} \leq \frac{\bar{\kappa}_*^2}{\mu_*}, \tag{45}$$

$$\delta_* e_* - \frac{\delta_* e_*^2}{4} \leq \frac{\delta_*^2}{\mu_*} \leq \frac{\bar{\delta}_*^2}{\mu_*}, \tag{46}$$

$$e_\theta e_\gamma \leq \frac{1}{2a_1} e_\theta^2 + \frac{a_1}{2} e_\gamma^2, \forall a_1 > 0, \tag{47}$$

$$e_Q e_\theta \leq \frac{1}{2a_2} e_Q^2 + \frac{a_2}{2} e_\theta^2, \forall a_2 > 0, \tag{48}$$

$$-e_\theta \dot{\alpha}_\gamma \leq \frac{1}{2a_3} e_\theta^2 + \frac{a_3}{2} \dot{\alpha}_\gamma^2, \forall a_3 > 0, \tag{49}$$

$$e_* \int_0^t e_* d\tau \leq \frac{1}{2a_4} e_*^2 + \frac{a_4}{2} \left(\int_0^t e_* d\tau \right)^2, \ \forall a_4 > 0, \tag{50}$$

Note that $\tilde{W}_i = W_i - \hat{W}_i$, we have

$$\begin{aligned} \tilde{W}_\gamma^T \hat{W}_\gamma =& \tilde{W}_\gamma^T \left(W_\gamma - \tilde{W}_\gamma \right) = \tilde{W}_\gamma W_\gamma - ||\tilde{W}_\gamma||^2 \\ \leq& -\frac{1}{2}||\tilde{W}_\gamma||^2 + \frac{1}{2}\|W_\gamma\|^2. \end{aligned} \tag{51}$$

$$\tilde{W}_Q^T \hat{W}_Q \leq -\frac{1}{2}||\tilde{W}_Q||^2 + \frac{1}{2}\|W_Q\|^2, \tag{52}$$

$$\operatorname{tr}\left\{ \tilde{S}_\gamma^T \hat{S}_\gamma \right\} \leq -\frac{1}{2}||\tilde{S}_\gamma||_F^2 + \frac{1}{2}\|S_\gamma\|_F^2, \tag{53}$$

$$\operatorname{tr}\left\{ \tilde{S}_Q^T \hat{S}_Q \right\} \leq -\frac{1}{2}||\tilde{S}_Q||_F^2 + \frac{1}{2}\|S_Q\|_F^2. \tag{54}$$

Substituting (45)-(54) into (44), and let $a = a_1 = a_2 = a_3 = a_4$, one has

$$\begin{aligned} \dot{V} \leq& -p_\gamma e_\gamma^2 - p_\theta {e_\theta}^2 - p_Q {e_Q}^2 - r_\gamma \left(\int_0^t e_\gamma d\tau \right)^2 \\ &-r_\theta \left(\int_0^t e_\theta d\tau \right)^2 - r_Q \left(\int_0^t e_Q d\tau \right)^2 - \frac{\sigma_\gamma}{2} \left\| \tilde{S}_\gamma \right\|_F^2 \\ &-\frac{\sigma_\gamma}{2} \left\| \tilde{W}_\gamma \right\|^2 - \frac{\sigma_Q}{2} \left\| \tilde{S}_Q \right\|_F^2 - \frac{\sigma_Q}{2} \left\| \tilde{W}_Q \right\|^2 + \upsilon, \end{aligned} \tag{55}$$

where

$$\begin{aligned} p_\gamma =& n_\gamma g_\gamma(\gamma, d_\gamma) k_\gamma - \frac{a}{2} g_\gamma(\gamma, d_\gamma) - \frac{1}{2a} c_\gamma + \frac{1}{2a} n_\gamma g_\gamma(\gamma, d_\gamma) c_\gamma, \\ p_\theta =& k_\theta - \frac{1}{2a} g_\gamma(\gamma, d_\gamma) + \frac{1}{2a} c_\theta - \frac{1}{2a} - \frac{a}{2} - \frac{1}{2a} c_\theta, \\ p_Q =& n_Q g_Q(\gamma, \theta, Q, d_Q) \left(\frac{c_Q}{2a} + k_Q \right) - \frac{1}{2a} - \frac{1}{2a} c_Q, \\ r_\gamma =& \frac{a}{2} n_\gamma g_\gamma(\gamma, d_\gamma) c_\gamma - \frac{a}{2}, \\ r_\theta =& \frac{a}{2} c_\theta - \frac{a}{2}, \\ r_Q =& \frac{a}{2} n_Q g_Q(\gamma, \theta, Q, d_Q) c_Q - \frac{a}{2}, \\ \upsilon =& g_\gamma(\gamma, d_\gamma) \frac{\bar{\kappa}_\gamma^2 + \bar{\delta}_\gamma^2}{\mu_\gamma} + g_Q(\gamma, \theta, Q, d_Q) \frac{\bar{\kappa}_Q^2 + \bar{\delta}_Q^2}{\mu_Q} + \frac{a}{2} \dot{\alpha}_\gamma^2 \\ &+ \frac{\sigma_\gamma}{2} \|S_\gamma\|_F^2 + \frac{\sigma_\gamma}{2} \|W_\gamma\|^2 + \frac{\sigma_Q}{2} \|S_Q\|_F^2 + \frac{\sigma_Q}{2} \|W_Q\|^2. \end{aligned}$$

From (55), it follows that

$$\dot{V} \leq -lV + \upsilon, \tag{56}$$

where $l = \min\{2p_\gamma, 2p_\theta, 2p_Q, 2r_\gamma, 2r_\theta, 2r_Q, \sigma_\gamma \Gamma_{W_\gamma}, \sigma_\gamma \Gamma_{S_\gamma}, \sigma_Q \Gamma_{W_Q}, \sigma_Q \Gamma_{S_Q}\}$.

Integrating both sides of (56) gives rise to

$$\begin{aligned} V(t) \leq& \left(V(0) - \frac{\upsilon}{l} \right) e^{-lt} + \frac{\upsilon}{l} \\ \leq& V(0) e^{-lt} + \frac{\upsilon}{l}. \end{aligned} \tag{57}$$

From (57), it can be seen that $V(t)$ is bounded with $\lim_{t\to\infty} V(t) = \frac{\upsilon}{l}$. Along the same lines as [22], we can conclude that all closed-loop signals can be ensured to be SGUUB in the presence of unknown periodic disturbances.

This completes the proof. ■

Remark 4: According to (39), we have $\frac{e_\gamma^2}{2} \leq V(t)$. Utilizing $\frac{e_\gamma^2}{2} \leq V(t)$ and (57), the inequality $\lim_{t\to\infty} e_\gamma \leq \sqrt{\frac{2\upsilon}{l}}$ holds. It is worth noting that $\frac{\upsilon}{l}$ can be arbitrarily reduced by increasing $\Gamma_{W_\gamma}, \Gamma_{S_\gamma}, \Gamma_{W_Q}, \Gamma_{S_Q}, k_\gamma, k_\theta, k_Q, \mu_\gamma, \mu_Q$ and c_γ, c_θ, c_Q or decreasing σ_γ, σ_Q. Based on (10), then the altitude tracking error will converge to a small neighbourhood of the origin.

5 Simulations

In the velocity subsystem,in order to achieve desired velocity tracking performance, we employ the PID controller in the form of

$$\Phi = k_P \Delta V + k_I \int \Delta V dt + k_D \Delta \dot{V}, \tag{58}$$

where $\Delta V = V - V_{ref}$, k_P, k_I and k_D are positive design parameters.

Apart from this, we consider the situation that unknown time-varying disturbances implicitly appear in the HFVs dynamics and the thrust force T is formulated as

$$\begin{aligned} T =& \beta_1(h, \bar{q}) \Phi \alpha^3 d_T + \beta_2(h, \bar{q}) \alpha^3 d_T + \beta_3(h, \bar{q}) \Phi \alpha^2 \\ &+ \beta_4(h, \bar{q}) \alpha^2 + \beta_5(h, \bar{q}) \Phi \alpha + \beta_6(h, \bar{q}) \alpha \\ &+ \beta_7(h, \bar{q}) \Phi + \beta_8(h, \bar{q}), \end{aligned} \tag{59}$$

where $d_T = |\sin(t)|$, and let $g_\gamma = \frac{\bar{q}S(C_L^\alpha + 0.5\sin(t))}{mV}$, $f_\gamma(\gamma, d_\gamma) = \frac{\bar{q}S[C_L^0 - (C_L^\alpha + 0.5\sin(t))\gamma] + T\sin\alpha}{mV} - \frac{g\cos\gamma}{V}$ and $g_Q = \frac{\bar{q}S\bar{c}(c_e + 0.1\sin(t))}{I_{yy}}$. The HFVs are supposed to climb a maneuver from the trim states, provided in Table 1, to final states V=8480ft/s and h=83800ft, respectively. The number of FSE components are set as $q_\gamma = q_\gamma = 5$, FSE-RBFNNs approximator ${W_\gamma}^T \psi_\gamma\left(\chi_\gamma, S_\gamma^T \phi\right)$ contain 5^3 nodes with centres evenly distributed in $[-2, 2] \times [-2, 2] \times [-2, 2]$ with the width being equal to two. FSE-RBFNNs approximator ${W_Q}^T \psi_Q\left(\chi_Q, S_Q^T \phi\right)$ contain 5^5 nodes with centres evenly distributed in $[-2, 2] \times [-2, 2] \times [-2, 2] \times [-2, 2] \times [-2, 2]$ with the width being equal to two. The design parameters are set: $k_P = 1$, $k_I = 0.1$, $k_D = 0.01$, $k_h = 10$, $k_i = 1$, $k_\gamma = 2$, $k_\theta = 5$, $k_Q = 7$, $\sigma_\gamma = \sigma_Q = 0.001$, $c_\gamma = c_\theta = c_Q = 1$ and $\mu_\gamma = \mu_Q = 1$. The adaptive gains are: $\Gamma_{S_\gamma} = \Gamma_{W_\gamma} = \Gamma_{S_Q} = \Gamma_{W_Q} = 1$. The initial values of $||\hat{S}_\gamma||$, $||\hat{W}_\gamma||$, $||\hat{S}_Q||$ and $||\hat{W}_Q||$ are set as zero.

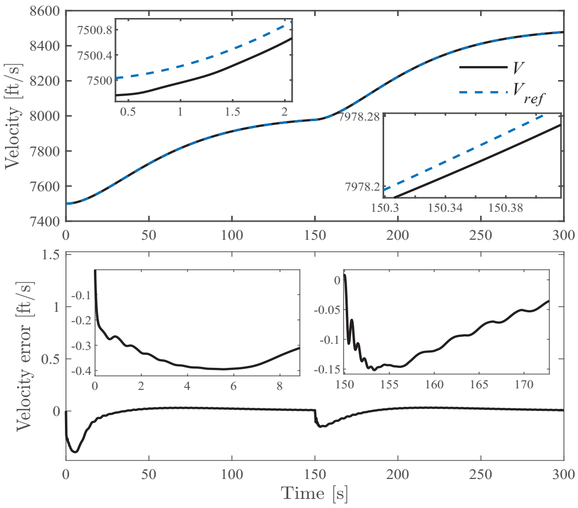

Fig. 1: Velocity tracking performance

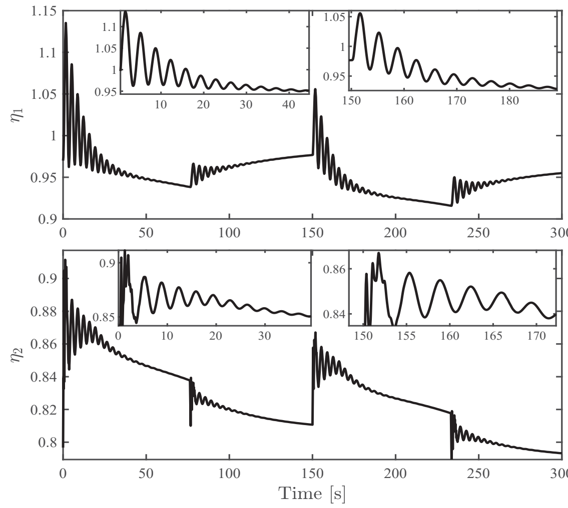

Fig. 4: The flexible states

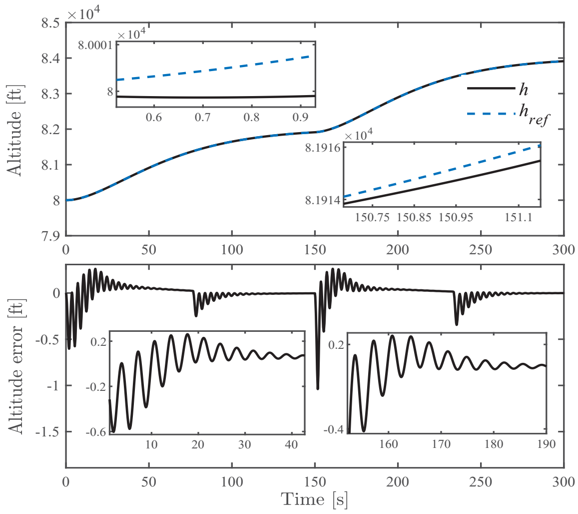

Fig. 2: Altitude tracking performance

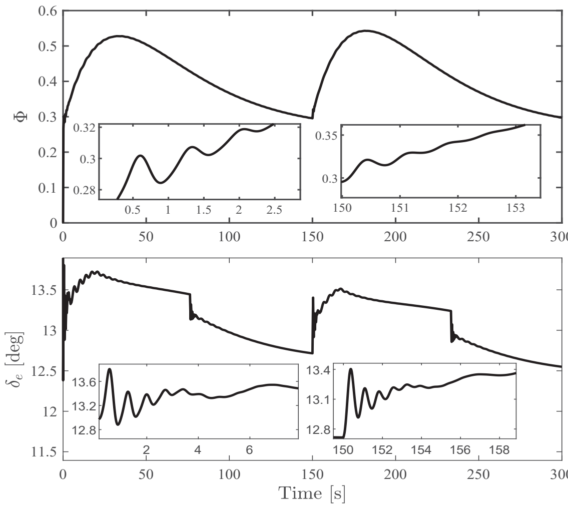

Fig. 5: The control inputs

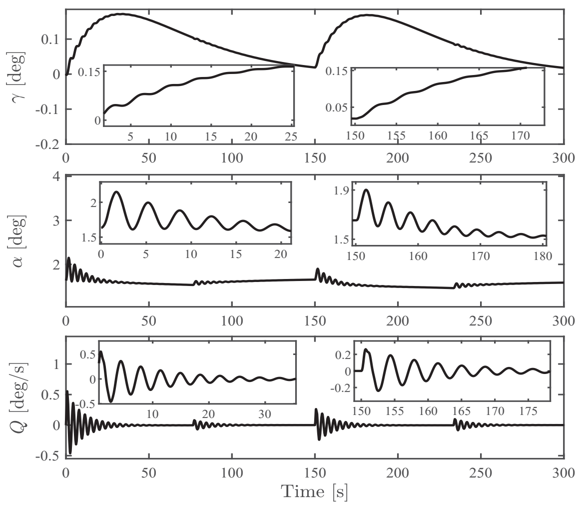

Fig. 3: The flight patch angle, attack of angle and pitch rate

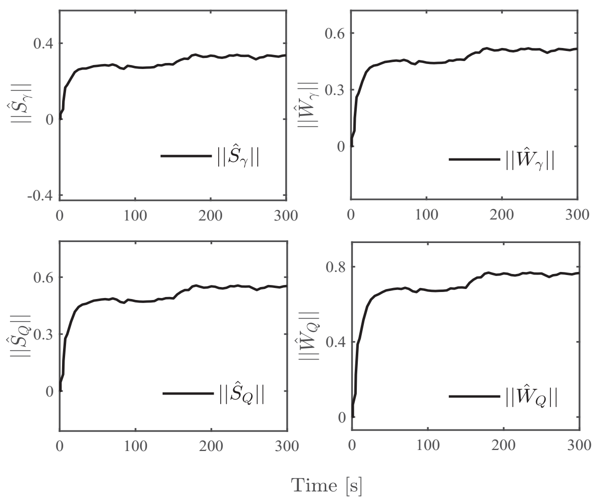

Fig. 6: Estimates of $||\hat{S}_\gamma||$, $||\hat{W}_\gamma||$, $||\hat{S}_Q||$ and $||\hat{W}_Q||$

Table 1: The initial states

States	Value	Units
V	7500	ft/s
h	80000	ft
γ	0	deg
θ	1.6325	deg
Q	0	deg/s
η_1	0.97	ft slugs$^{0.5}$/ft
$\dot{\eta}_1$	0	ft/s slugs$^{0.5}$/ft
η_2	0.7967	ft slugs$^{0.5}$/ft
$\dot{\eta}_2$	0	ft/s slugs$^{0.5}$/ft

The HFVs model parameters are borrowed from [18]. The simulation results are shown in Figs.1-6. The velocity and altitude tracking performance, depicted in Fig.1 and Fig.2, show that the tracking error can rapidly converge to a residual set after selecting proper design parameters. From Fig.3 and Fig.4, it can be seen that the flight path angle, attack of angle, pitch rate and flexible states are bounded as well as within a reasonable range. The responses of Φ and δ_e are presented in Fig.5 and no chattering phenomenon occurs. It is observed from Fig.6 that $||\hat{S}_\gamma||$, $||\hat{W}_\gamma||$, $||\hat{S}_Q||$ and $||\hat{W}_Q||$ are bounded. Overall, simulation results verify the validity of the developed control strategy.

6 Conclusion

This paper for the first time addresses the tracking control problem for the longitudinal dynamics of HFVs in the presence of uncertain periodic time-varying disturbances. The challenge of tackling such class lies in the occurrence of perturbations in flight dynamics. To pursue this, a new approximator consisting of FSE and RBFNNs is adopted to estimate the uncertain dynamics involving periodic disturbances. Simulation results validate the effectiveness of the developed control strategy.

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